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Prognostication of environmental indices in potato production using artificial neural networks

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A B S T R A C T

Artificial Neural Network (ANN) is an appropriate tool for forecasting the non-linear relationships across many scientific studies. In this study a back-propagation (BP) learning algorithm was chosen to predict the environmental indices of potato production in Iran. Data were collected randomly from 260 farms in Fereydonshahr city, located in Esfahan province by face to face questionnaire method. Initially, Life cycle assessment (LCA) methodology was developed to assess all the environmental impacts associated with potato cultivation in the studied region. The six LCA indices including global warming potential (GWP), eutrophication potential (EP), human toxicity potential (HTP), terrestrial ecotoxicity potential (TEP), oxidant formation potential (OFP) and acidification potential (AP) were selected as target outputs. Farm gate and one tone of potato produced were chosen as system boundary and functional unit. To find the best topology, several ANN models with different number of hidden layers and neurons in each layer were developed. To assess the best performance, a topology with highest coefficient of determination (R^2), lowest root mean square error (RMSE) and mean absolute error (MAE) was selected as optimum architecture. Accordingly, ANN model with 11–10–6 structure showed the best performance. RMSE for GWP, HTP, EP, OFP, AP and TEP was computed as 0.037, 0.005, 0.057, 0.032, 0.048 and 0.037, respectively. Also, MAEs for this model were calculated as 0.028, 0.001, 0.039, 0.022, 0.035 and 0.027 for GWP, HTP, EP, OFP, AP and TEP, respectively. Evaluation of the results revealed that the developed ANN model (11–10–6 architecture) appears to be appropriate tool in predicting environmental indices of potato production.

1. Introduction

Potatoes are grown worldwide under a wide range of altitude, latitude, and climatic conditions than any other major food crop. No other crop can match the potato in its production of food energy and food value per unit area (Zangeneh et al., 2010). This plant has one of the heaviest demands for fertilizer inputs over other crops. For instance, the percentage of nitrogen (N), phosphorus (P) and potassium (K) requirement for potato cultivation are, respectively, 100, 100 and 33% greater than that required for tomato or pepper production (Mohammadi et al., 2008).

Energy balance of crop production was much debated in the early 1970s when the world energy crisis made people aware that the supply of fossil energy is limited (Pimentel et al., 1973). Factors such as population growth, limited supply of arable land and desire for higher standard of living cause energy consumption increase dramatically (Tabatabaie et al., 2012). Agriculture is both a producer and consumer of energy. It uses large quantities of locally available non-commercial energies, such as seeds, manure and livestock energy, and commercial energies directly and indirectly (Pishgar Komleh et al., 2011). Efficient use of energies helps to achieve increased production and productivity and contributes to the economy, profitability and competitiveness of agriculture sustainability in rural areas (Singh et al., 2002).

Energy related missions account for over two thirds of the anthropogenic greenhouse gases (GHG) emissions (Taseska et al., 2011). Global warming, as one of the most important issues in the recent century, is the continuing rise in the average temperature of Earth's atmosphere and oceans and is caused by increased concentrations of greenhouse gases (GHGs) in the atmosphere, resulting from human activities such as deforestation and burning of fossil fuels (Pathak and Wassmann, 2007). Agricultural GHG emissions account 10–12% of all manmade GHG emissions (Pishgar-Komleh et al., 2012). Production, transportation, storage, distribution and application of the inputs with machinery in agricultural activities lead to combustion of fossil fuel and use of energy

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from alternate sources, which also emits GHGs and other pollutants in to the atmosphere (Lal, 2004).

Life cycle assessment (LCA) is a methodology for assessing all the environmental impacts associated with a product, process or activity, by identifying, quantifying and evaluating all the resources consumed, and all emissions and wastes released into the environment (Rebitzer et al., 2004). LCA has of late been more widely applied in agricultural and industrial fields, and a great deal of reports are available on its use for analyzing agricultural products (i.e. wheat, sugar beet and maize) and cropping systems' impacts on the environment (Avraamides and Fatta, 2008; Brentrup et al., 2004a, 2004b; Cellura et al., 2012; Ingwersen, 2012; Ntiamoah and Afrane, 2008). Life cycle assessment of bean production in the Prespa National Park was investigated by Abeliotis et al. (2013). In another study carried out by Roy et al. (2007), Life cycle of rice was evaluated to determine environmental load and production cost of rice in Bangladesh. Life cycle assessment of Italian citrus-based products was studied by Beccali et al. (2010).

In the last few decades, artificial neural networks (ANNs) have been widely used in different fields of agriculture like economic, energy and environmental modeling as well as to extend the field of statistical methods, in the last few decades. The advantage of ANNs over statistical methods is reported in Zhang et al. (1998). The main reason that ANN applications have received considerable attention is that the methodology is comparable to statistical modeling and ANNs could be faced as complementary effort (without the restrictive assumption of a particular statistical model) or an alternative approach to fitting non-linear data (Özçelik et al., 2010). Of statistical models, ANN, which relates input–output variables without explicit information on the processes causing the response, has been widely used for describing complex non-linear relationships across many scientific studies (He et al., 2011).

Ermis et al. (2007) analyzed world green energy consumption through ANNs. They analyzed world primary energy including fossil fuels such as coal, oil and natural gas, using feed forward back propagation ANN. Rahman and Bala (2010) employed ANNs to estimate jute production in Bangladesh. In their study, an ANN model with six input variables including Julian day, solar radiation, maximum temperature, minimum temperature, rainfall, and type of biomass was applied to predict the desired variable (plant dry matter). Pahlavan et al. (2012) developed ANNs for prediction of greenhouse basil production. Safa and Samarasinghe (2011) used ANNs for determination and modeling of energy consumption in wheat production. They compared ANNs with Multiple linear regression (MLR) and found that ANNs can predict energy consumption better than MLR models.

Based on the literature, there has been no study on environmental emissions modeling for potato production with respect to input energy flow using ANN. The purpose of this study was to model field emissions of potato production in different impact categories – global warming potential (GWP), human toxicity potential (HTP), eutrophication potential (EP), ecotoxicity potential (ETP), acidification potential (AP) and oxidant formation potential (OFP) – using ANNs in order to predict the environmental indices of this production in Esfahan province of Iran.

2. Materials and methods

2.1. Data collection and processing

Data for this study was collected from rural regions of Esfahan; a central province of Iran located within 30–42° and 34–30° north latitude and 49–36° and 55–32° east longitude. The province with a total production of 345 kton from 14,591 ha is considered as one of the main fertile regions in producing potatoes in Iran. The sample size was calculated using the Neyman method as the following:

$$n = \frac{\sum(N_h S_h)}{N^2 D^2 + \sum N_h S_h^2} \tag{1}$$

where n is the required sample size; N is the number of farmers in the target population; N_h is the number of the farmers in the h stratification; S_h^2 is the variance of the h stratification; d permitted error ratio deviated from average of population $(\bar{x} - \overline{X})$, z is the reliability coefficient (1.96 which represents 95% confidence); $D^2 = d^2/z^2$; the permissible error in the sample population was defined to be 5% within 95% confidence interval (Rafiee et al., 2010). Accordingly, the sample size was determined to be 260, so 260 potato producers were randomly selected and interviewed.

The common agricultural practices to yield potatoes in the area of which the study was carried out were: field preparation (plowing, disk harrowing and leveling of the soil), incorporating farmyard manure into the soil, seeding, post-seeding agricultural practices, fertilization, irrigation (water extracted from local wells by means of electrical pumps), spraying pesticide, plant protection and harvesting. Above-mentioned cultivation processes along with energy and materials consumed during crop treatment were regarded as LCA steps. Life cycle inventory (LCI) data for potato production is summarized in Table 1.

As it can be observed in the last row of Table 1, the results of impact assessment are in terms of m^2 of annual cultivated land ($m^2\ a^{-1}$).

Converting all input materials used in potato production into their energy equivalents necessitates the application of energy conversion factors (energy coefficients) manifested in Table 2. To aim at obtaining each energy equivalent discretely, the input materials; used per hectare (ha), were multiplied by their equivalent energy conversion factors. The acquired energy equivalents were later applied by artificial neural networks for modeling at the final stage. As it can be seen in Table 2, agricultural machineries were categorized in three groups. Using the following formula machinery energies were estimated (Kitani, 1999):

$$\mathrm{ME} = \frac{ELG}{TC_a} \tag{2}$$

where 'ME' is the machine energy (MJ ha^{-1}), 'G' the weight of machine (kg), 'E' the production energy of machine (MJ $kg^{-1}\ yr^{-1}$) that is shown in Table 2, 'L' the useful life of machine (year), 'T' the economic life of machinery (h) and 'C_a' the effective field capacity (ha h^{-1}).

Table 1
Life cycle inventory data for potato production.

Inputs	Units	Average	Max	Min	SD
Machinery	kg	4675.05	5117	3917	261.6
Labor	h	175.84	360	68.6	88.51
Diesel fuel	L	76.18	98.5	31.5	14.5
Electricity	kWh	2545.48	4504.59	525.54	992.35
Chemical fertilizers					
Nitrogen (N)	kg	301.74	500	100	82.62
Phosphate (P_2O_5)	kg	190.6	400	120	78.21
Potassium (K_2O)	kg	84.32	150	75	55.71
FYM[a]	kg	7794.75	15,000	0	7597.74
Pesticides	kg	2.47	6.67	0	1.03
Water for irrigation	m^3	5231.07	9257.14	1080	2039.33
Seed	kg	3490.74	4000	2833.3	187.98
Land use	$m^2\ a^{-1}$	16,333.3	50,000	2000	12,302.3

[a] Farmyard manure.